Frontiers in Genetic and Evolutionary Computation (2019) 1: 1-4
Clausius Scientific Press, Canada
DOI: 10.23977/fgec.2019.11001
ISSN 2523-0166

Mixed Particle Swarm Optimization Algorithm with Multistage Disturbances

Wang Peng

School of Economics and Management, Dalian University, No.10, Xuefu Avenue, Economic & Technical Development Zone, Dalian, Liaoning, The People's Republic of China(PRC)

Keywords: Particle swarm optimization algorithm, Mixing, Multi-level perturbation, Local optimal value, Ergodic ability

Abstract: In order to solve the problem that the particle swarm optimization algorithm is easy to fall into the local optimal value, a hybrid particle swarm optimization algorithm with multi-level perturbation is proposed. The algorithm combines the advantages of two classical improved particle swarm optimization algorithms, namely the standard with inertial parameters. Based on the particle swarm optimization algorithm and the particle swarm optimization algorithm with shrinkage factor, a multi-level perturbation mechanism is introduced. When the particle position is updated, the first-order perturbation is introduced to enhance the traversal ability of the particle to the solution space. In the case of “local optimal”, a second-order perturbation is introduced, which causes the optimization process to continue, thus getting rid of the local optimal value. Six test functions are used - Sphere function, Ackley function, Rastrigin function, Styblinski-Tang function, Duadric Function and Rosenbrock function to the proposed. The hybrid particle swarm optimization algorithm is used for simulation and comparison verification. The simulation results show that the proposed hybrid particle swarm optimization algorithm is better than the other two classic improvements in the simulation of the test function. Particle swarm optimization algorithm; in addition, when dealing with multimodal functions, the algorithm is not easily limited by local optimal values.

1. Introduction

The particle swarm optimization algorithm is an evolutionary algorithm developed by Kennedy and Eberhart in 1995 to simulate the bird's foraging characteristics. In the algorithm, the particles represent the individual birds in the foraging. When each particle moves, consider the whole The optimal position of the group and the optimal position that the current particle has experienced, similar to the information exchange between the birds when the birds feed. When all the particles in the group move, it is recorded as a round of optimization iteration, then proceed A round of optimization iterations until the preset iteration depth or other conditions are met. The entire group, like a bird foraging, always moves toward the optimal position[1].

The above various PSO-based improvements and post-adaptation optimization algorithms have their own advantages, but in general they all try to solve the inherent problem of the original PSO algorithm - easy to fall into local extremum. For this problem, the research is based on The existing two classical improved PSO algorithms can avoid the problem that the PSO algorithm is easy to fall into the local optimal value by introducing a multi-level perturbation strategy without excessively increasing the time complexity of the algorithm. At the same time, different perturbations can be used to deal with the PSO algorithm. The algorithm has poor exploration ability or early convergence of the algorithm. In the research, the performance of the algorithm is tested by Sphere, Ackley, Rastrigin, Styblinski-Tang, Duadric and Rosenbrock functions, and the results of different PSO correlation optimization algorithms are compared and verified. The improved PSO algorithm proposed in this study subtly combines the characteristics of two classical improved particle swarm optimization algorithms (particle swarm optimization with inertia weight and shrinkage factor), so that the algorithm can combine the two optimization algorithms. The advantages are maximized. At the same time, for the problem of easy to fall into the local optimum, a multi-level disturbance mechanism is proposed. Overall, the calculation Not only can it increase the ability of particles to explore the solution space, but also better jump out of the local optimum. This paper first introduces the above two classical improved particle swarm optimization algorithms in Section 1. Then, it is described in detail in Section 2. The new improved PSO algorithm, the concept and flow of the hybrid particle swarm optimization algorithm. In Section 3, the feasibility and accuracy of the hybrid particle swarm optimization algorithm is applied by the combination of four test functions. Contrast and verification. Finally, the algorithm and related particle swarm optimization algorithms are discussed, and the subsequent research is prospected[2].

2. Traditional Particle Swarm Optimization Algorithm

2.1 Particle Swarm Optimization

The particle swarm optimization algorithm originally proposed in the process of simulating bird foraging, the position information of each particle represents a possible solution in the solution space, and the velocity information represents the renewal (moving) dynamics of the particle. The initial particle swarm optimization algorithm It can always be updated efficiently, thus reflecting the characteristics of fast convergence.

Assume that the population size of the problem to be optimized is n, the dimension of the solution space is m, the position of each particle in the population is Xi (i = 1, 2, ..., n), and the fitness value of each particle is f (Xi)(i=1,2,...,n), the position of the i-th particle in the kth generation is kXi, the velocity of the particle is kVi, and the optimal adaptation of the i-th particle

2.2 Standard Particle Swarm Optimization

The general idea of the SPSO algorithm is that each particle in the particle group has its own position and velocity. Each iteration is equivalent to updating the position and velocity of each particle in the group, the speed of the particle is updated and the particle's previous speed and itself. The historical optimal position and the optimal position of the group history are related to the difference of the current position. The position update of the particle is related to the speed. The SPSO algorithm is characterized by adding an inertia weight to the inheritance ability of the particle. The ability of the particle history velocity attribute to influence the current attribute. The main idea is that the global search ability of the particle swarm is stronger than the local search ability by the large inertia weight at the beginning of the optimization algorithm, and the algorithm is continuously iteratively optimized. After that, the local search ability of the particle swarm is gradually strengthened by reducing the inertia weight.

3. New Hybrid Particle Swarm Optimization Algorithm with Multi-Level Disturbance

Both SPSO and PSOCF improved optimization algorithms have their own characteristics. In particle swarm optimization, different parameters affect different aspects of the algorithm: inertia weight affects the inheritance of particle attributes in the algorithm; and compression factor not only affects inheritance, More affects the convergence of the overall algorithm. Compression factor too Large, the convergence is poor, and the algorithm is close to random search optimization; if the compression factor is too small, it is easy to converge early, resulting in the result may be local optimal value, and the precision is degraded. Inspired by layering the particles, the new improvement proposed in this study Algorithm-a hybrid particle swarm optimization algorithm with multi-level perturbation is to integrate the advantages of the above two optimization algorithms. Based on the consideration that particles can inherit their own optimal solutions and group optimal solutions, multi-level is introduced. Disturbance to increase the randomness of particle position variation and prevent premature convergence of particles.

The particle swarm optimization algorithm has the characteristics of fast convergence, which makes the algorithm easy to fall into the local optimal value and cause the error in the final optimization result. Therefore, multi-level disturbance is introduced in this study to prevent premature convergence. The multi-level perturbation strategy is divided into two levels: The main role of the level disturbance is to make the particles more fully Traversing the solution space, similar to chaotic perturbation, is to increase the traversal ability of the particle; the second-order perturbation is an auxiliary strategy proposed to cope with the problem of easily falling into the local optimal value in the case of multi-peak, and improve the accuracy of the search result. Similar to bees looking for honey. Currently looking for the best, but still need to go elsewhere to explore whether there is more honey, then assume that the optimal position of food at this moment has been exhausted, as The basis is to find other foods. The first-order disturbance is introduced after the particle update position. The specific introduction probability is related to the current iteration depth (Tc) and the maximum iteration depth (Tm) [3-5].

4. Algorithm Simulation Experiment

Through simulation experiments, the above four functions are optimized and tested: the global extremum of the function is defined as the optimal value; three particle swarm optimization algorithms (hybrid particle swarm optimization algorithm, standard particle swarm optimization algorithm and shrinkage factor) are used. Particle swarm optimization algorithm) performs optimization operations; in the algorithm.

Set the four step dimensions (5, 10, 15 and 20, indicating the number of particles in the optimization algorithm) to perform the calculation separately; the termination condition for a single optimization is 2 000 iterations; the number of experiment repetitions is 10, taking the average The values compare different settings and scenes (functions). The first three functions-the Sphere function, the Ackley function, and the Rastrigin function-have zero for their global minimum, so the optimization effect of the optimization algorithm is based on the accuracy of its final optimization result value. The specific comparison results are shown in Table 5. The global minimum of Styblinski-Tang is not 0, so the optimization result is expressed by the deviation between the algorithm optimization value and the function extreme value.

5. Conclusions

Aiming at the problems that the classical particle swarm optimization algorithm is easy to fall into local optimum and the convergence speed is slow, this paper proposes a hybrid particle swarm optimization with multi-level perturbation based on the analysis of two classical particle swarm optimization algorithms SPSO and PSOCF. Algorithm. The original particle swarm optimization algorithm is multi-partial.

In the extreme case, it is easy to fall into the local optimal value. The SPSO and PSOCF algorithms are formally improved for this feature. The MPSO algorithm proposed in this study combines the advantages of these two classical improved optimization algorithms and introduces a multi-level perturbation strategy. , using multi-level disturbances to interfere with the particle exploration process.

In addition to its own speed and positional update, the particle obtains a kind of “vibration”, which not only increases the ability of the algorithm to explore near the local extremum, but also expands the ability of the algorithm to escape when it falls into the local optimal value. When the algorithm converges in time, the exploration ability and the accuracy of the optimal value of the particle swarm optimization algorithm are greatly improved.

Acknowledgement

This article was specially funded by Dalian University's 2019 Ph.D. Startup Fund (20182QL001) and 2019 Jinpu New District Science and Technology Project.

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